# A Multiagent Interaction Paradigm for Physiological Process Control

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## ABSTRACT

Multiagent systems are powerful and flexible tools for controlling complex phenomena. The complexity of a phenomenon can be tackled in such a way that each agent embeds the controller for a portion of the phenomenon [3]. In this perspective, the interaction among the agents results in a complex controller for the whole phenomenon. The actions the agents undertake to control their portions of the phenomenon may conflict, as a result of the "overlapping" of the controlled portions; hence a mediated interaction is needed. A class of complex phenomena that present several difficulties in their satisfactory modeling and controlling is the class of physiological processes.

We illustrate the negotiation paradigm of a general regulating multiagent architecture called anthropic agency.

## Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: Multiagent Systems.
I.2.8 [**Problem Solving, Control Methods, and Search**]: Control Theory. J.3 [**Life and Medical Sciences**]: Health.

## General Terms

Algorithms, Design, Experimentation.

## Keywords

Physiological Process Control, Anthropic Agency, Negotiation, Glucose-Insulin Metabolism.

## 1. INTRODUCTION

We developed a general multiagent architecture, called *anthropic agency*, for the control of complex physiological phenomena. According to the anthropic agency approach, a multiagent control and regulation system operates in three major steps: knowledge extraction, decision making, and plan generation (see Fig. 1). Each one of these steps is carried on by a group of agents and the interactions between these groups are mediated by shared memory areas called *blackboards* [7].

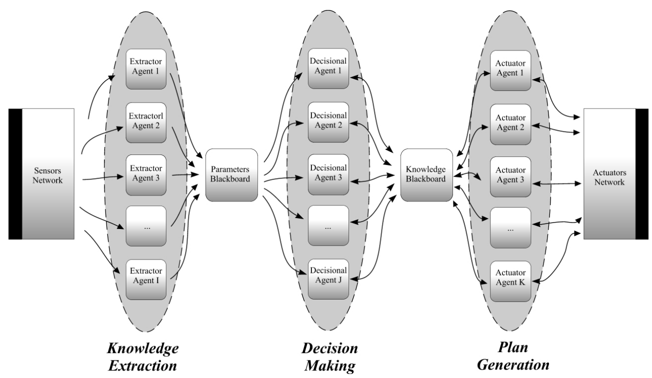


**Figure 1. The general anthropic agency architecture.**

Within this approach, we have defined a negotiation paradigm the agents adopt to agree on a global decision from their possibly conflicting partial views. In particular, the *decisional agents* embed the models of particular physiological processes and decide what to do on the basis of their internal models, of the current values of parameters (read form the *parameters blackboard* filled by the *extractor agents*), and of the effects of the past decisions. A component of the knowledge blackboard, called *equalizer*, mediates among these decisions as described in the following section.

## 2. THE NEGOTIATION MECHANISM

A *decision* taken by a decisional agent is a pair: a desirable state and a weight. The weight is a measure of how much the decisional agent "wants" to reach the proposed state. The control models embedded in the decisional agents are all different, but they may overlap in two ways: the intersection of the input parameters and the intersection of the output proposed decisions could be not null. The decisional agents are not directly connected to each other, but they are all connected to a shared memory area, the *knowledge blackboard*, where they put their decisions. By the interactions among the decisional agents, a complex physiological process is regulated.

The equalizer reads the decisions from the knowledge blackboard and operates in order to optimize the social welfare. The social welfare evaluation mechanism involves the decisions of the decisional agents with their weights, the *costs*, and the *importance* of the decisional agents. The costs involved in the negotiation process are three. The *variation cost* expresses how much the desired state is far from the current state. This cost is locally determined by each decisional agent. The *actuation cost* expresses how difficult is for the *actuator agents* to reach the desired state from the current state (this means that also the actuator agents participate to the negotiation process). Finally, the *negotiation cost* expresses the measure of the difficulty to change a single parameter according to the desires of the other decisional agents. This cost is determined by the equalizer and then communicated to the decisional agents (Fig. 2 summarizes the messages involved in the negotiation mechanism). The importance of the decisional agents discriminates between the decisional agents that control life functions and those that control less important functions; the importance depends on the current state parameter values.

The negotiation process is a cyclic repetition of two phases: in the first one each decisional agent determines a single desired state (from the set of possible ones) in order to minimize the sum of the variation, actuation, and negotiation costs; in the second one, the equalizer calculates the new negotiation costs according to the received decisions. Then, the process restarts with the decisional agents that receive the new negotiation costs and express the new decisions. In addition, every fixed amount of time (30*s* in our implementation) the equalizer communicates the current weighted averages of the negotiated parameters (the agreed-upon target state) to the actuator agents that plan the actions and send back to the decisional agents the actuation costs. In this way, a unique final decision that maximizes the social welfare is determined.

According to [4], we defined both the agents decision making models and the rules that govern the interaction that allows the agents to agree on the final target state to reach. The negotiation mechanism we adopted belongs to the class of data fusion paradigms [1] [5].

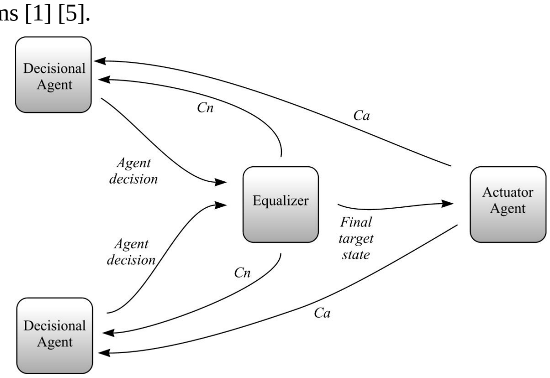


**Figure 2. A schematic representation of the messages involved in the negotiation mechanism (*Ca* and *Cn* are the actuation and the negotiation costs, respectively).**

## 3. CONCLUSIONS

To test the anthropic agency approach and its negotiation mechanism, we have implemented a regulation system for glucose-insulin metabolism. The human metabolism of is simulated by a simulator system with the introduction of some disturbs to check the response of the control system. Thus the control system tries to keep the glucose concentration of a simulated diabetic patient as close as possible to the concentration of an healthy person.

Our implementation is constituted by an extractor agent, two decisional agents, and an actuator agent. The first decisional agent embeds a simplified control model of the glucose metabolism related to food adsorption [2]: it tries to reduce the glucose concentration during food adsorption. The second decisional agent embeds a simplified control model of the glucose metabolism related to physical activity [6]: it tries to keep constant the glucose level by limiting the hexogen insulin introduction when the physical activity is intense. The actuator agent acts on an insulin infusion pump. We have implemented the anthropic agency as a collection of Java objects connected via RMI.

The experimental activity has verified the correct functioning of the negotiation mechanism that stabilizes the insulin and glucose levels in the patient (see Fig. 3 for an example).

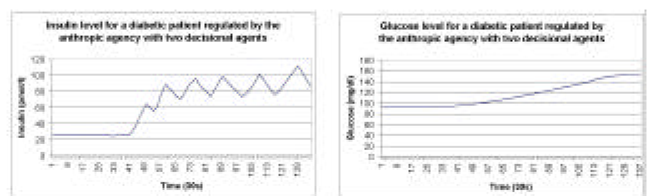

**Figure 3. The insulin and glucose curves of a diabetic patient when absorbing food and undergoing a physical activity.**

The definition of the anthropic agency architecture and of its negotiation mechanism is only the first step of a more comprehensive project that aims to employ multiagent techniques to control physiological processes. The long term goal of the project is the implementation of the anthropic agency in wearable computers and robots that can be employed to control the physiological processes of a real persons.

## 4. ACKNOWLEDGMENTS

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